Advanced and Sustainable Technologies
ASET
E-ISSN 2976-2294
Volume 5, No 1, June 2026 [154-166]

A Digital Twin Framework for Corrosion Predictive Analysis

Noor Ul Eeman[1]*, Wasim Ahmad[1], Mirza Jahanzaib[1] and Salman Hussain[1]

[1]Faculty of Industrial Engineering, University of Engineering and Technology, Taxila, Pakistan.

Received 1 January 2026, Revised 12 February 2026, Accepted 25 February 2026

ABSTRACT

In today's dynamic environment, digital twins are gaining attraction for predictive maintenance. Existing research lacks the solutions that integrate advanced computer vision with intuitive visualization for corrosion analysis. This study aims to develop a Digital Twin framework for predictive corrosion analysis to improve asset integrity and operational performance from an Industry 4.0 perspective. The proposed framework focuses on offshore and onshore oil and gas platforms. In order to automatically identify the corrosion, YOLOv8 and YOLOv11 object detection models have been used to pre-process and analyze a curated corrosion dataset. The findings of the study reveal that with 93.6% accuracy and an F1-score of 0.92, YOLOv11 performs better than YOLOv8 (88.1% accuracy and 0.71 F1-score). It demonstrates the robustness of the YOLOv11 in diverse platform environments. Further, in the proposed Digital Twin framework, a corrosion data visualization dashboard has been designed to convert detection outputs into practical insights. The dashboard comprises corrosion severity indicators, spatial mapping, and performance metrics, enabling support for Reliability-Centered Maintenance (RCM) and Risk-Based Inspection (RBI). The study contributes to knowledge by benchmarking state-of-the-art detection models and presenting a corrosion-focused Digital Twin framework that integrates AI-enabled sensing with decision-support visualization.

Keywords: Corrosion, Data Visualization Dashboard, Digital Twin framework, Predictive Corrosion Analysis, YOLOv11.

1. INTRODUCTION

Digital Twin Technology is being widely adopted in the industrial sector as Industry 4.0 progresses. Digital replicas of real-time systems, products, and landscapes are found to increase productivity, enhance operational efficiency, and reduce cost overruns in the manufacturing, healthcare, energy, and industrial sectors. The existing literature also highlights the substantial benefits of digital twin technology across the stated factors of efficiency, cost, and innovation. A survey study by Gulewicz [1] showed that 32% of enterprises were on the side to implementing DT technology in their organizations, and 50% believed that the technology would improve the efficiency of processes. However, 64% still believed that this technology needs to be developed further; this difference shows that there is a need for a deeper understanding of the technology and its deployment.

A study conducted by Oettl [2] highlights the need for the development of a structured cost estimation model for the deployment of DT technology and for quantifying expenses in the industrial sector. However, the study highlights a comprehensive framework for assessing the financial implications of DT implementation, which hinders organizations from adopting this technology and making informed decisions.

---

*Corresponding author: noorulееman468@gmail.com

1.1 Digital Twin in Industry 4.0

The digitization technology of Industry 4.0 aimed at the creation of smart factories with the interconnected systems communicating and cooperating both internally and across the organizational boundaries, which makes the production systems flexible and responsive to the dynamic changes [3], [4]. With the integration of AI and ML into the digital twin, the capacity for autonomous adaptation and optimization is further increased, leading to efficiency improvements and productivity enhancements [5], [6]. The major applicability of the DT Technology is in Predictive Maintenance and asset management, which facilitates the construction of virtual replicas and their continuous update with real-time data and dynamic innovation technologies. This practice in the manufacturing sector results in a 30% reduction in maintenance costs and a5% increase in equipment uptime [7]. DT Technology facilitates better collaboration among stakeholders in the construction industry by enhancing project planning, design optimization, and real-time monitoring of virtual building replicas. In the automotive sector, DT Technology has reduced the development cycle by 15% and prototyping costs by about 20% [8].

1.2 Digital Twin Development Historical Background

Data visualization dashboards have become vital tools for condition assessment in the oil and gas industry, aggregating heterogeneous data from sensors, inspection logs, and machine learning models into accessible formats for decision-making. Onuegb [9] highlighted dashboards as key enablers of predictive maintenance, enabling operators to visualize corrosion-related key performance indicators (KPIs) such as wall-thickness loss, corrosion rates, and remaining useful life in intuitive charts and heatmaps. Similarly, a study by Dia [10] showed that anomaly detection models can be visualized as color-coded maps which pinpoint corrosion hotspots, and Sarwar [11] merged finite element models with deep learning predictions, emphasizing the need for user-friendly interfaces to convert computational results into actionable engineering knowledge. Digital twins, when used in RCM, allow continuous assessment of equipment health and enhance efficiency and asset life. The technology promotes more confident maintenance scheduling, optimized spare parts inventory, and safer, evidence-based interventions [12]. Within the framework of RBI, digital twins improve the inspection regimes, shifting it to dynamic (condition-based) from the previous (static, based on a calendar). Historical trends and failure rates are combined with real-time operational data to continuously update the risk profile [13]. A study proposed by Bevilacqua [14] in 2020 shows current research data on dynamic simulation models used in process hazard analyses, and offers a framework to help design, develop, and implement a Digital Twin that is dedicated to risk management, providing a possible prospect of a Digital Twin to model an actual production factory, and anticipate the risky scenarios. A study by Bhandari [15] has established a spatial digital twin framework for the oil and gas project field design in Australia, incorporating the Land Survey Data Model (LSDM) and capable of storing and representing spatial information within a 3D environment.

2 PROPOSED FRAMEWORK

The study focuses on the development of a digital twin framework within an Industry 4.0 environment. This framework, which is a product of holistic reviews, outlines a methodical cycle of life that ensures the passage of raw data gathering to actionable decision support, scalability, interoperability, and real-time responsiveness. This study adopted a modular methodology for developing a digital framework and embedding it into a maintenance management software. The proposed framework is structured into five modules, including: (i) data acquisition and sensor integration module, (ii) 3D model reconstruction and semantic representation module, (iii) engineering data integration model validation module, (iv) condition monitoring, anomaly detection, and diagnostic analytics module, and (v) predictive analytics, optimization, and decision support module. The detailed structure of the proposed module is shown in Figure 1. The following sections provide the details of each module.

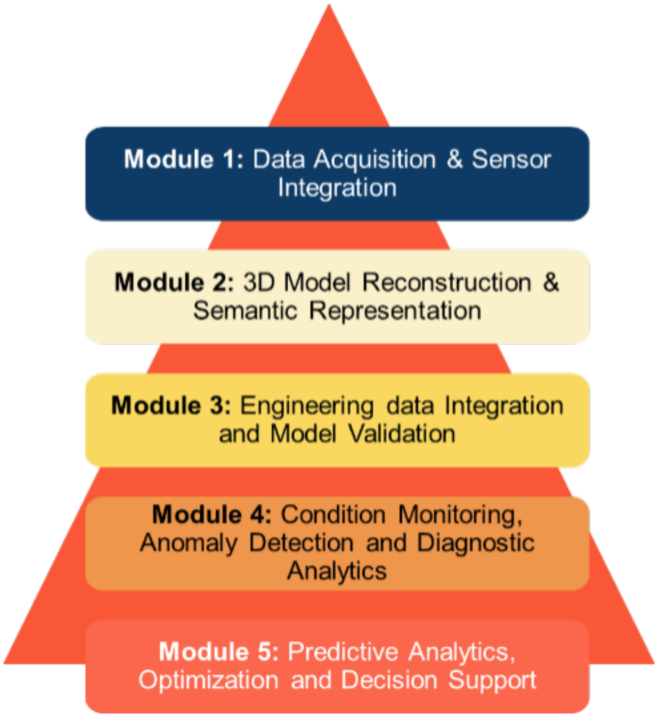


Figure 1: Architecture of the proposed digital twin development framework for corrosion analysis.

2.1 Data acquisition and sensor integration module

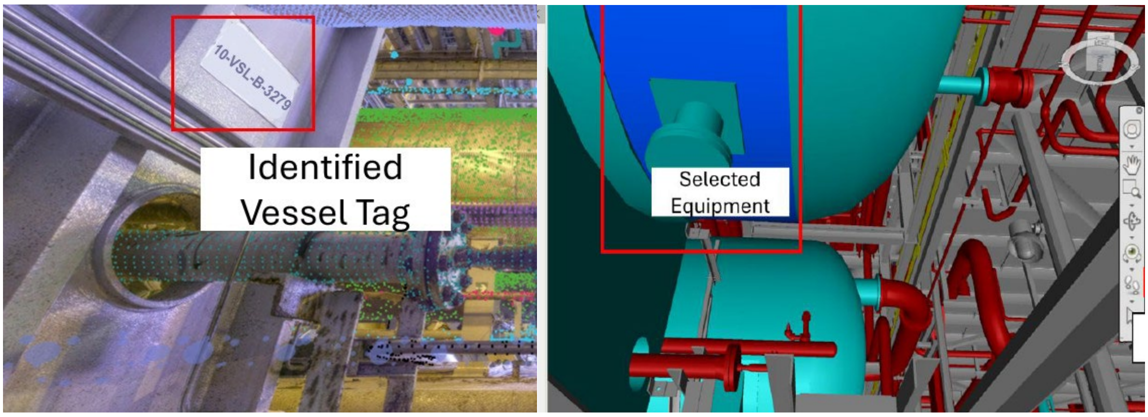
A study by Bongomin [16]demonstrates the need to integrate heterogeneous data sources to facilitate real-time monitoring and decision-making. For this purpose, this module used an automation photogrammetry-based scanning system to acquire the detailed and system spherical visual information. In this module, a dataset is curated from the scan, so each sphere provides a complete spatial context.

2.2 3D model reconstruction and semantic representation module

Based on a scan of module 1, a 3D model is reconstructed in module 2 using semantic segmentation, assigning classes to assets such as pressure vessels, pipelines, valves, and pipe supports. The next step after segmenting classes is to tag them based on their verified information, as referenced in engineering documents. A study conducted by Istvan [17] demonstrates that standards such as IFC and ISO 15926 interoperability play a key role in standardizing various engineering data, enabling easy exchange between CAD, BIM, and DT.

2.3 Engineering data integration model validation module

In this module, semantic data was tagged to the true identifiers using CAD for spatial and dimensional accuracy, and verified through CAD and GA drawings to assign asset IDs for tracking each asset with precision within the digital twin structure (Figure 2).



(a) (b)

Figure 2: Digital twin asset integration and verification module 3. (a) Onsite Asset Identification from Onsite labelled Data (b) Verification of Vessel through CAD from the spherical positioning in PCD.

2.4 Condition monitoring, anomaly detection, and diagnostic analytics module

In module 4, condition monitoring, anomaly detection, and diagnostic analytics (corrosion instances) are simulated and labelled using a computer vision algorithm that references previously annotated datasets. In the digital twin, corrosion severity is shown by combining detection results with information embedded in the tagged mesh model (Figure 3).

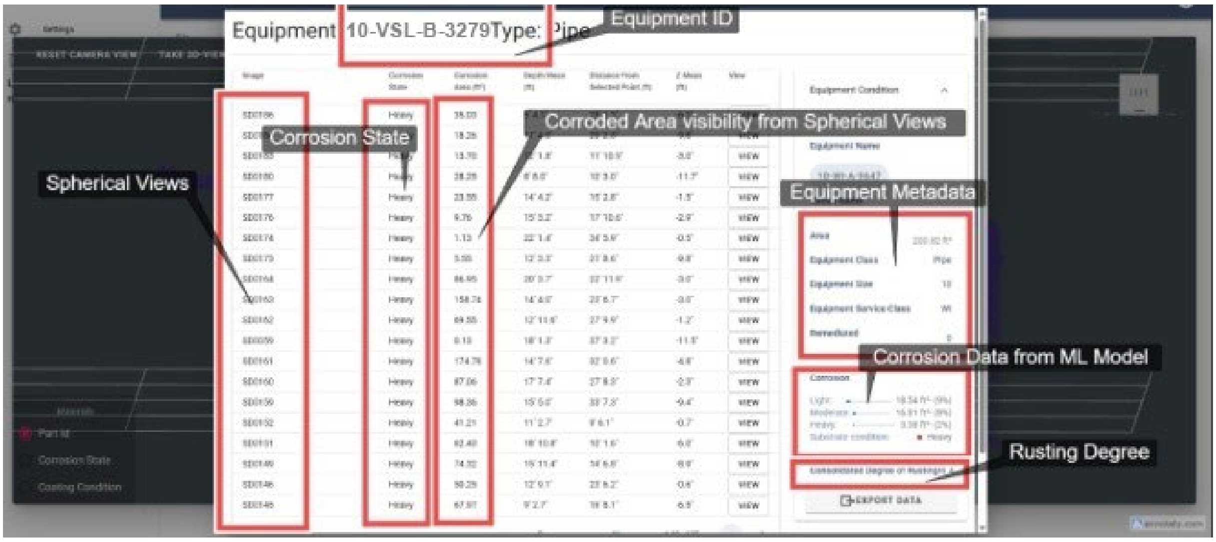


Figure 3: Condition monitoring, anomaly detection and diagnostic analytics module 4: metadata of the equipment under inspection (single/multiple).

2.5 Predictive analytics, optimization, and decision support module

Research conducted by Kerkenihas [18] pointed out that good predictive analytics can help to cut unplanned outages by 30%, which is why it is important in a competitive industrial ecosystem. That's why, in module 5 of this study, the data have been integrated into an interactive dashboard. Digital twin visualization and predictive intelligence present all the information from the previous modules, allowing inspection engineers to interactively observe, evaluate, and confirm corrosion conditions on different offshore rig components [19]. This dashboard enables easy navigation from 3D-scanned data to on-site 3D rig visualization for real-time data access and sound decision-making.

3 APPLICATION OF MACHINE LEARNING

To minimize reliance on manual inspection, AI-integrated models trained on diverse datasets for corrosion identification and monitoring are being employed to cut operational costs, reduce lead time, and reduce reliance on human capacity [20]. To employ the most successful method of risk-based inspection (RBI) for offshore and onshore rigs, a comparative analysis is conducted between the YOLOv8 and YOLOv11 algorithms. The detailed workflow of dataset training and evaluation under the machine learning approach is described in Figure 4.

4 RESULTS AND DISCUSSION

The dataset curated for corrosion training and analysis comprises 4,949 images across three classes: Crevice, Pitting, and Uniform Corrosion. The data is split into 90% (training), 8% (validation), and 2% (testing) (Figure 4). The results obtained are shown in the confusion metrics (Figure 5).

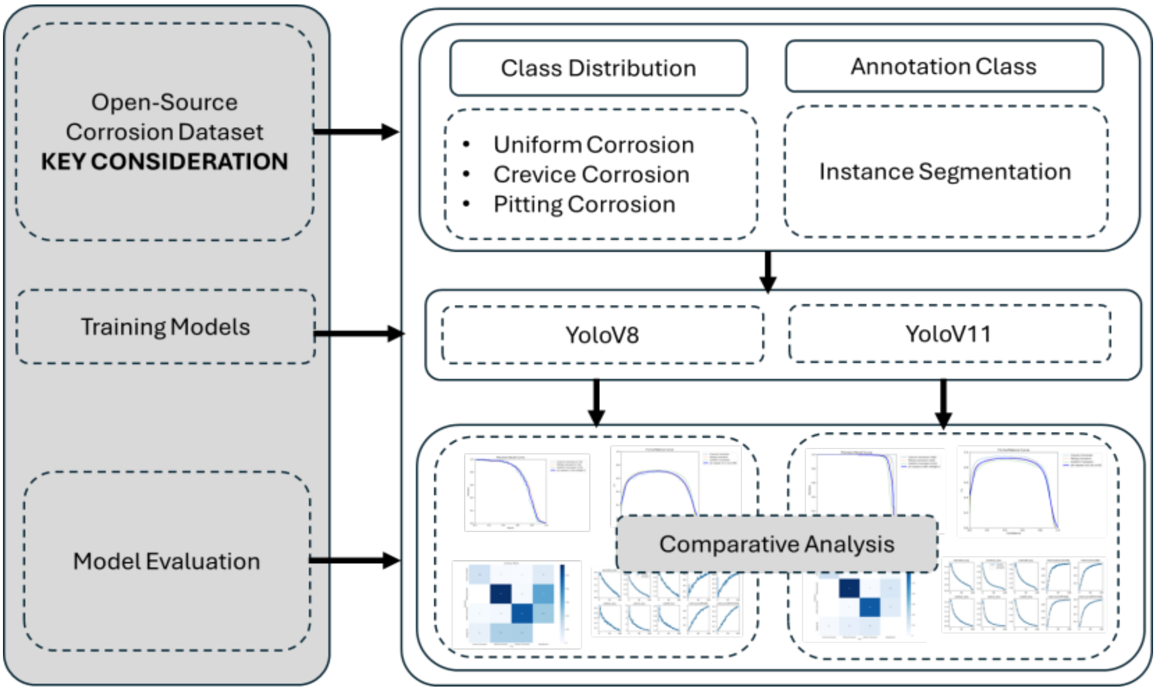
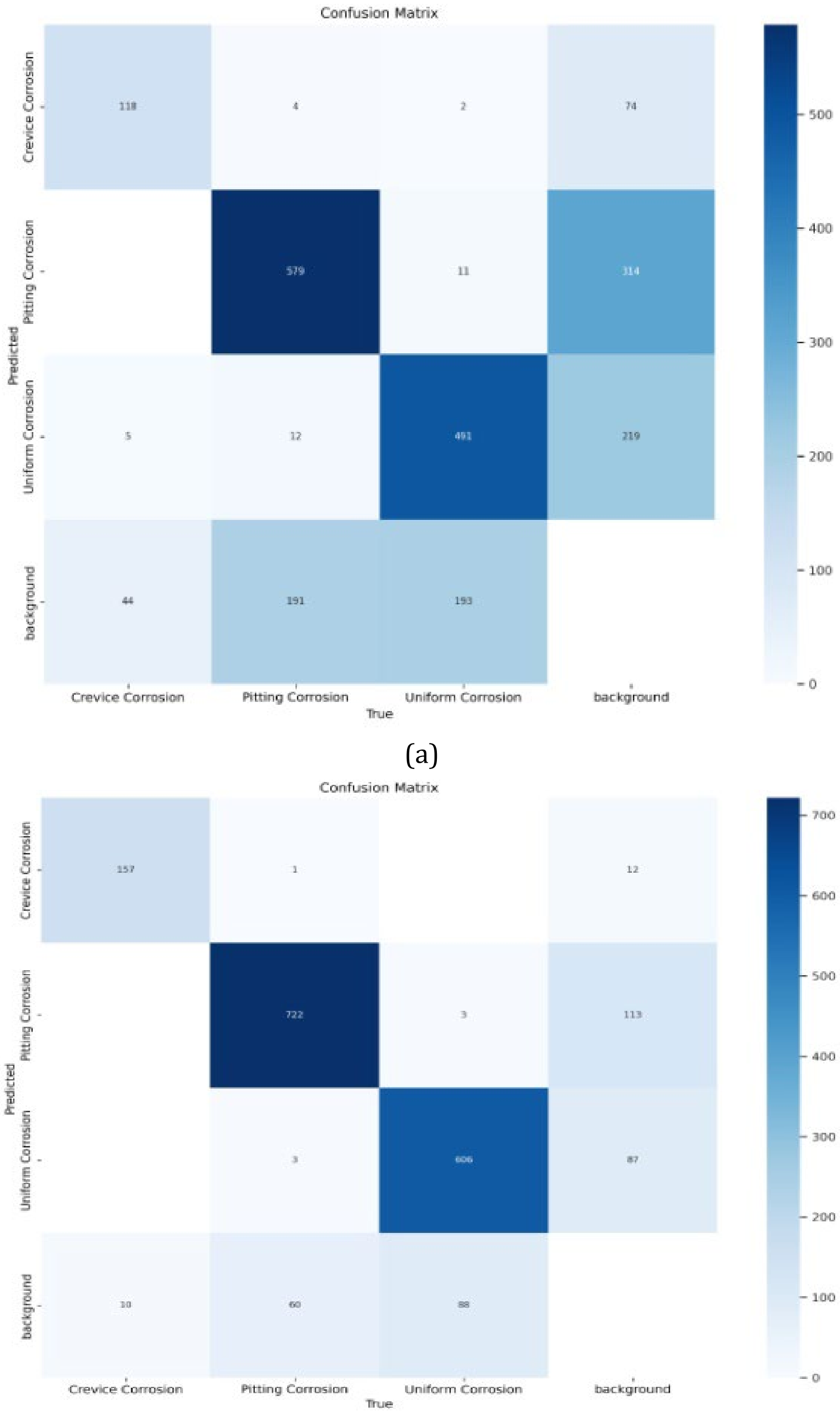


Figure 4: Dataset training and evaluation workflow.

The confusion matrix shows that YOLOv8 struggles to distinguish between corroded and non-corroded areas. In many cases, the background class was identified as corrosion. In 193 cases, 100% were falsely marked as uniform corrosion, leading to more false alarms in real use. In comparison, YOLOv11 shows much better ability in detecting different classes. It effectively identified the correct cases in 157 instances of crevice corrosion, and only 12 background cases were incorrectly identified. It shows a noticeable improvement in avoiding false negatives. Further, the confusion matrix summarizes the comparative analysis as depicted in Table 1.



(a)

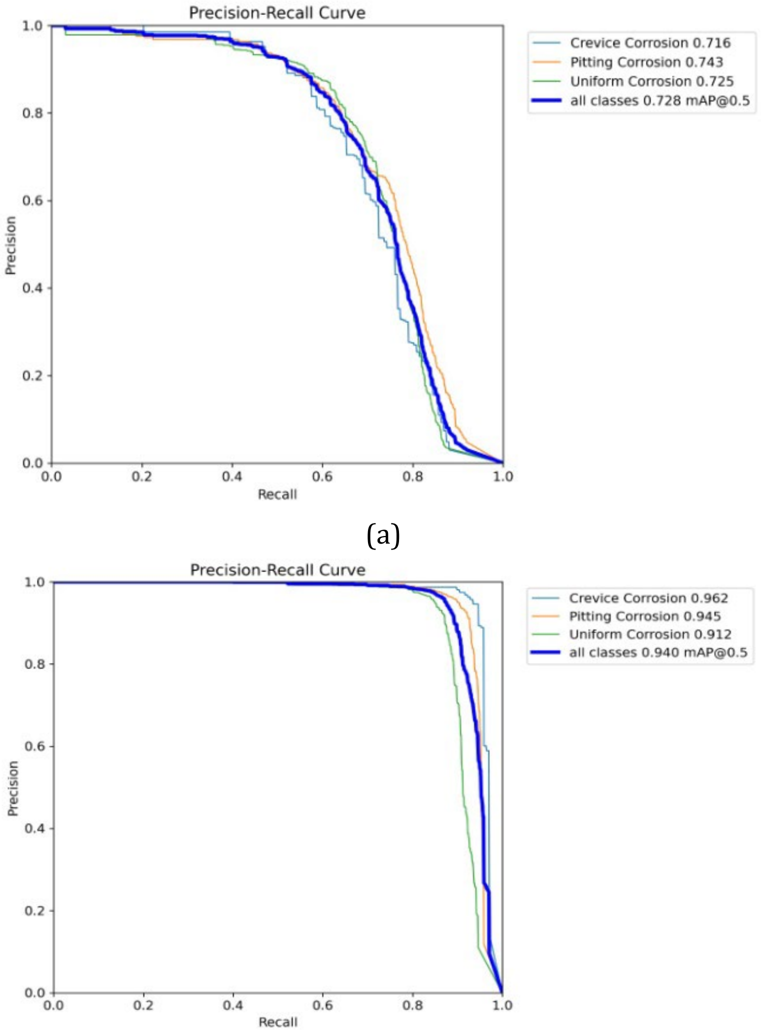
(b)

Figure 5. Confusion matrix: (a) YoloV8, (b) YoloV11.

From Figure 6, it can be seen that the graph values for each class are well balanced, ranging from 0.71 to 0.74. As more instances are retrieved, precision decreases, leading to more false positives. Models meet the threshold, but there is still potential to improve both accuracy and the ability to handle new cases.

Table 1: Confusion matrix for comparative analysis of corrosion using Yolov8 and Yolov11 algorithms.

Classes	YOLOv8	YOLOv11
Crevice Corrosion	118 correctly predicted 74 confused as background (High False Negative)	157 correctly predicted 12 confused as background (Improved Significantly)
Pitting Corrosion	579 Correct 314 confused as background (High Confusion)	722 Correct 113 confused as background (Better Separation)
Uniform Corrosion	491 Correct 219 confused as background (Moderate Confusion)	606 Correct 87 confused as background
Background	Misclassified corrosion types 193 predicted as Uniform Corrosion	Low false positive 88 Predicted as Uniform Corrosion

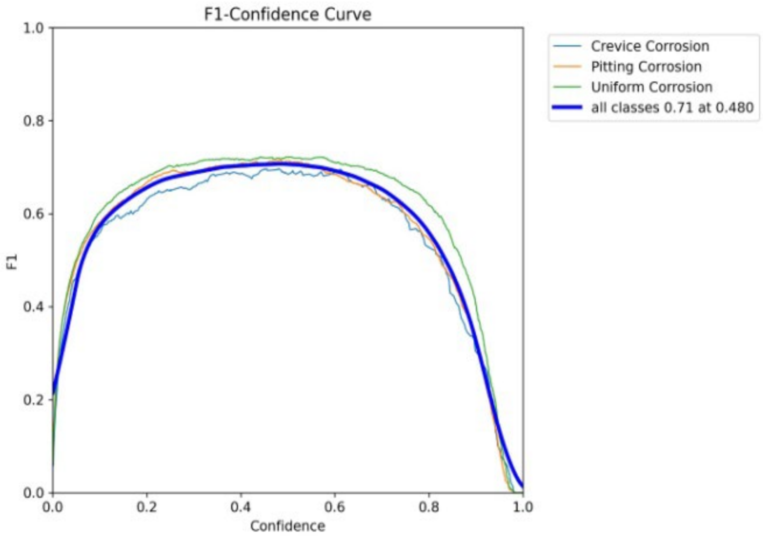


(a)

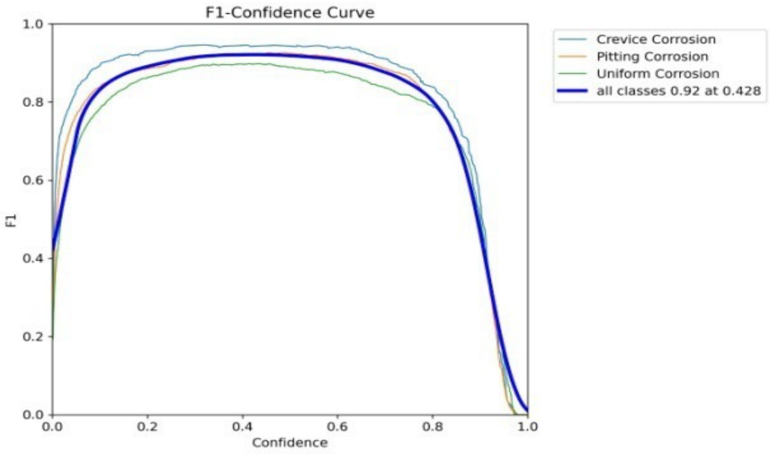
(b)

Figure 6: Precision recall curves (a) YoloV8 (b) Yolov11.

In Figure 7, the best F1 score for YOLOv8 occurs at a confidence threshold of 0.48, with a score it 0.71. YOLOv11 performs much better than YOLOv8, achieving a maximum F1 score of 0.92 at a lower confidence of 0.428. It turns out that all three corrosion types achieve high, stable F1 scores, and crevice corrosion especially ranks high, reversing YOLOv8’s results. Overall results from both models are depicted in Table 2.



(a)



(b)

Figure 7: F1-Confidence Curves (a) YoloV8 (b) Yolov11.

Table 2: Outcomes of Yolov8 and Yolov11 algorithms in terms of accuracy, precision, recall, and confidence.

Algorithm	**Accuracy**(%)	**Precision**	**Recall**	**mAP** @0.5	**mAP** (0.5 -0.95)	**F1 Score**	**Training Time**(Sec)
YOLOv8	88.1	0.802	0.638	0.728	0.501	0.71	1,947.6
YOLOv11	93.6	0.949	0.895	0.94	0.789	0.92	11,250

5 FRAMEWORK VALIDATION

In order to validate and demonstrate the ability of the proposed framework to solve industry problems of asset reliability, downtime reduction, and operational efficacy, a conceptual interactive dashboard has been developed in this study, as shown in Figure 8. It supports the predictive analysis of corrosion asset data in a selected case study. The model is developed in light of the potential issues experienced by the industry:

i. Manual corrosion identification and inspection.
ii. Structured inspection framework.

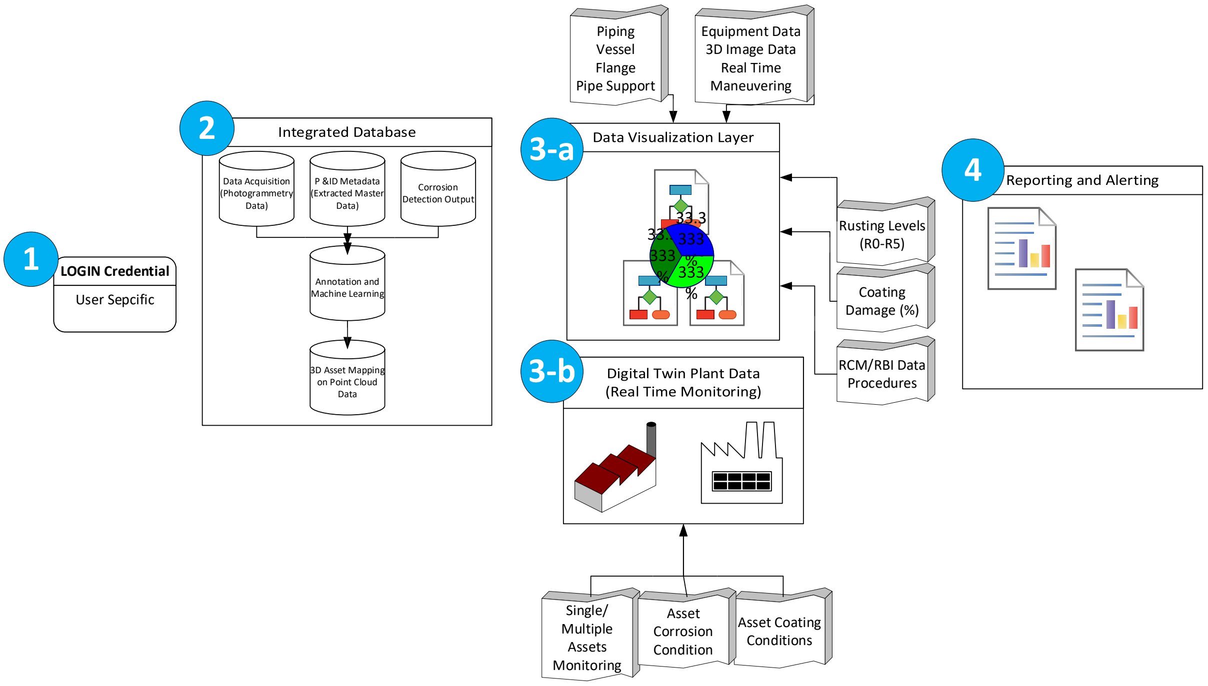


Figure 8: Digital twin-based corrosion monitoring dashboard for the selected industry.

The proposed corrosion monitoring and visualization system is a structured and integrated design to support secure access, controlled data processing, advanced visualization, real-time digital twin features, and actionable reporting/alerting to improve the integrity management of assets at risk in corrosion-prone settings (piping, vessels, and other infrastructure). The key components and workflow of the system architecture are depicted in Figure 8.

5.1 User Authentication Layer

Access to the system is triggered by secure, user-specific login credentials. This will provide authenticated, role-based access to data, securing sensitive data on assets and enabling customized access based on user privileges.

5.2 Integrated Database

After authentication, the system is linked to a centralized Integrated Database that consolidates data from various sources. This includes:

- Piping support and vessel data.
- Equipment metadata
- Real-time flange and piping information.
- Historical and annotated corrosion inspection data.
- Point cloud and 3D models derived from digital twins.

The database serves as central storage, balancing structured metadata (e.g., material composition, coating types, operating conditions) with unstructured or semi-structured information from inspections and monitoring.

5.3 Digital Twin Layer and Data Visualization

The visualization elements are separated into two related sub-layers:

- **3-a: Data Visualization Layer -** This provides interactive, geospatial, and analytical displays of corrosion-related parameters. It displays elements such as:
    - Rusting (e.g., severity categorization)
    - Coating damage extent
    - General asset status indicators.

These are displayed with intuitive interfaces, such as charts, heat maps, and superimposed indicators, on asset layouts or 3D models, making them easy to assess and analyze to determine trends.

- **3-b: Digital Twin Data (Real-Time Monitoring)** This layer uses a digital twin platform to establish a living, virtual copy of physical objects (e.g., visualized schematically as industrial facilities or monitoring systems). It combines real-time sensor feeds, inspection output, and predictive models to reflect the present condition of assets in real time. The digital twin enables an immersive 3D representation of corrosion development, localization of damage, and temporal condition changes.

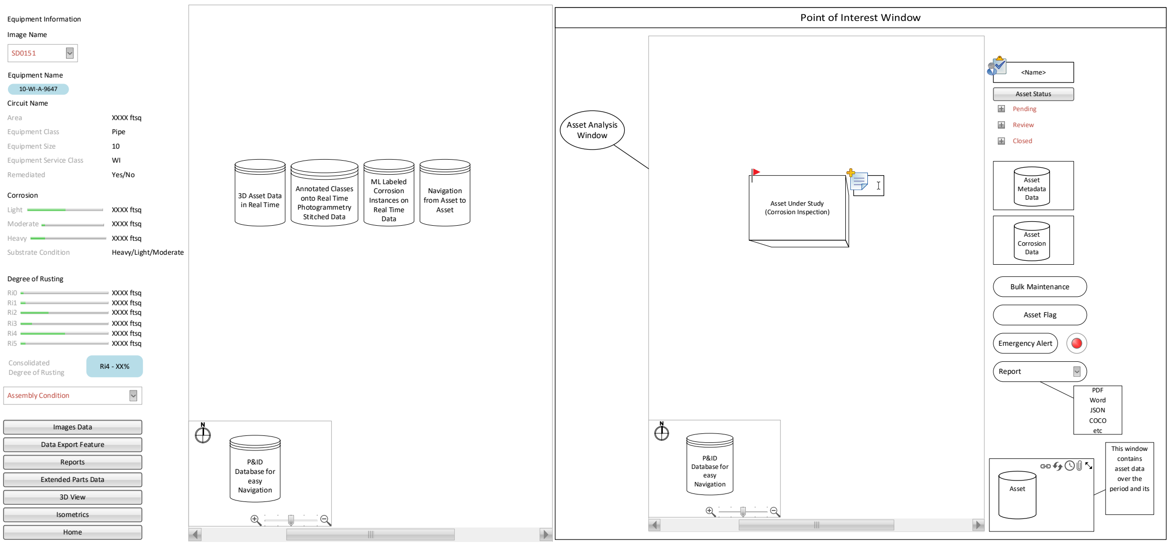
i. Reporting and Alerting Module

The outputs from the visualization and digital twin layers are consumed by the full Reporting and Alerting capabilities (Figure 9). This includes:

- Creation of individual or multiple asset reports.
- Corrosion state reports.
- Rusting and asset coating analyses.
- Alerts about critical degradation (e.g., high level of rust or coating failures) using thresholds.

The reports may be exported in different formats (e.g., PDF and dashboards) and help to make better decisions about maintenance planning, prioritization, and compliance.

This architecture addresses weaknesses of traditional manual inspection by offering an integrated, data-driven platform which integrates secure access, unified data storage, advanced visualization (including 3D digital twin representations), real-time monitoring, and proactive alerting/reporting. It facilitates efficient corrosion detection, joint inspection, and informed decision-making in asset management, ultimately improving safety, reliability, and operational lifespan in industrial contexts.



(a) (b)

Figure 9: Conceptual framework of digital twin integrated corrosion monitoring dashboard (a) Window containing on-site and metadata integrated reporting for assets of the case study(b) window contains reporting and assessment to track progress and updated records for real-time emergency notification.

6 CONCLUSION

This research work aimed at evaluating the contribution of digital twin technologies to enhance the performance in the Industry 4.0 environment, for corrosion monitoring in the oil and gas industry. The research managed to combine theoretical foundations, experimental validation, and framework development in a structured multi-phase approach to meet the objectives.

i. First, the study demonstrated the value of digital twins as a means of improving asset integrity and operating reliability, thereby demonstrating their relevance to predictive maintenance and risk-based decision-making.
ii. Second, a comparative analysis of YOLOv8 and YOLOv11 was performed, where YOLOv11 outperformed YOLOv8 across all performance metrics, including accuracy, precision, recall, and F1-score, and thus demonstrated itself as a more robust model for corrosion detection in offshore and onshore environments.
iii. Third, the research proposed a comprehensive conceptual model for a corrosion data visualization dashboard, serving as a blueprint to integrating computer vision outputs into decision support systems. This dashboard delivers actionable feedback for Reliability Centered Maintenance (RCM) and Risk-Based Inspection (RBI), enabling engineers/inspectors to make informed decisions based on automated corrosion detection.
iv. Finally, the study demonstrated that by incorporating AI-driven corrosion detection into the digital twin platform, a viable route to digitizing traditional inspection methods into automated, more efficient corrosion surveillance could be realized. In doing so, the research adds value both academically by benchmarking YOLO models and furthering digital twin frameworks, and by providing engineers with a blueprint for real-world implementation in Industry 4.0 environments.

The results of the study affirm that a combination of computer vision and digital twin technologies can dramatically improve asset integrity management, operational efficiency, and decision-making in the oil and gas industry. Future work includes expanding the dataset and augmenting digital twins with additional sensing modalities, such as ultrasonic, infrared, and thermal imaging, to provide a more comprehensive and reliable view of corrosion states.

ACKNOWLEDGEMENTS

This research is part of the ongoing GetInnovative4Impact project. All the authors greatly acknowledge the support of ERASMUS for funding this project and the Department of Industrial Engineering for their technical and administrative support.

REFERENCES

[1] Gulewicz, M. Digital twin technology — awareness, implementation problems and benefits. Engineering Management in Production and Services, vol 14 (2022).
[2] Oettl, F., Eckart, L., Schilp, J. Cost estimation approach of a digital twin implementation in industry. Procedia CIRP, vol 118 (2023) pp.318–323.
[3] Vasilyeva, A., Kuznetsova, M., Zinovyeva, E., Kuznetsova, N., Ageeva, I. Estimation of the cost of developing a digital twin using virtual reality technologies in the metallurgical industry. Lecture Notes in Networks and Systems, vol 942 LNNS (2024) pp.66–77.
[4] Kritzinger, W., Karner, M., Traar, G., Henjes, J., Sihn, W. Digital twin in manufacturing: A categorical literature review and classification. IFAC-PapersOnLine, vol 51, issue 11 (2018) pp.1016–1022.
[5] Tao, F., et al. Digital twin-driven product design framework. Int. J. Prod. Res., vol 57, issue 12 (2019) pp.3935–3953.
[6] Klingenberg, C. O., Borges, M. A. V., Antunes, J. A. d. V. Industry 4.0: What makes it a revolution? A historical framework to understand the phenomenon. Technol. Soc., vol 70 (2022).
[7] Wahab, N. H. A., et al. Systematic review of predictive maintenance and digital twin technologies challenges, opportunities, and best practices. PeerJComput. Sci., vol 10 (2024).
[8] Zhang, C., Tao, F. Evaluation index system for digital twin model. JisuanjiJicheng Zhizao Xitong/Computer Integrated Manufacturing Systems, CIMS, vol 27, issue 8 (2021) pp.2171–2186.
[9] Onuegb, V., et al. Predictive maintenance in oil and gas facilities, leveraging ai for asset integrity management. International Journal of Frontiers in Engineering and Technology Research, vol 6, issue 1 (2024) pp.016–026.
[10] Dia, A. K., Ghazzali, N., Bosca, A. G. Unsupervised neural network for data-driven corrosion detection of a mining pipeline. Proceedings of the International Florida Artificial Intelligence Research Society Conference, FLAIRS, vol 35 (2022).
[11] Sarwar, U., et al. Enhancing pipeline integrity: a comprehensive review of deep learning-enabled finite element analysis for stress corrosion cracking prediction. Engineering Applications of Computational Fluid Mechanics, vol 18, issue 1 (2024).
[12] Rebello, C. M., Jäschkea, J., Nogueira, I. B. R. Digital twin framework for optimal and autonomous decision-making in cyber-physical systems: Enhancing reliability and adaptability in the oil and gas industry. (2023).
[13] Almessabi, A., Al-Saedi, K., Ddin, M. U., Al Naqbi, M. Transformation of operations through digital twin application. Society of Petroleum Engineers - ADIPEC, ADIP 2023 (2023).
[14] Bevilacqua, M., et al. Digital twin reference model development to prevent operators' risk in process plants. Sustainability 2020, vol 12, issue 3 (2020).
[15] Bhandari, S., Paudyal, D. R., Chadalavada, S. Spatial digital twin architecture for the field design process of oil and gas projects in Australia. Land (Basel). , vol 13, issue 7 (2024).
[16] Bongominet, O., et al. Digital twin technology advancing Industry 4.0 and Industry 5.0 across sectors. Results in Engineering, vol 26 (2025).

[17] Istvan, D., Guodong, S., Claudio, G., Dawn, T. Interoperability of digital twins: Challenges, success factors, and future research directions. (2025).

[18] Kerkeni, R., Khlif, S., Mhalla, A., Bouzrara, K. Digital twin applied to predictive maintenance for Industry 4.0. J. Nondestruct. Eval. Diagn. Progn. Eng. Syst., vol 7, issue 4 (2024).

[19] Wärmefjord, K., Söderberg, R., Schleich, B., Wang, H. Digital twin for variation management: A general framework and identification of industrial challenges related to the implementation. Applied Sciences 2020, vol 10, issue 10 (2020).

[20] Fadzil, N. M., et al. A hybrid fem-cnn for image-based severity prediction of corroded offshore pipelines. E3S Web of Conferences, vol 612 (2025).

Conflict of interest statement: The authors declare no conflict of interest.

Author contributions statement: Conceptualization, Noor Ul Eeman; Methodology, Noor Ul Eeman; Guidance through research from Dr. Wasim Ahmad and Dr. Salman Hussain; Formal Analysis, Noor Ul Eeman, Investigation, Noor Ul Eeman; Resources, Noor Ul Eeman; Data Curation, Noor Ul Eeman; Original Draft Preparation, Noor Ul Eeman; Writing-Review and Editing, Dr. Wasim Ahmad and Dr. Salman Hussain; Supervision, Dr. Wasim Ahmad and Dr. Salman Hussain; Project Administration, Dr. Wasim Ahmad; Guidance and Academic Oversight, Dr. Mirza Jahanzaib.

Declaration of Generative AI Use: During the preparation of this work, the author(s) used an AI tool to improve readability and language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.